

UNIVERSITY OF TECHNOLOGY, SYDNEY

Model-Aided State Estimation for Quadrotor Micro Aerial Vehicles

by

Dinuka Malin Wickramasinghe Abeywardena

A thesis submitted in partial fulfillment for the
degree of Doctor of Philosophy

in the
Faculty of Engineering and IT
Centre of Autonomous Systems

February 2015

Declaration of Authorship

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Signature of Student:

Date:

UNIVERSITY OF TECHNOLOGY, SYDNEY

Abstract

Faculty of Engineering and IT
Centre of Autonomous Systems

Doctor of Philosophy

by Dinuka Malin Wickramasinghe Abeywardena

Due to their manoeuvrability, compactness and vertical take-off and landing capability, quadrotor Micro Aerial Vehicles (MAV) are ideally suited to assist or replace humans in a host of tasks in urban and indoor environments that would otherwise be hazardous, tedious or expensive. However, obtaining reliable pose estimates to perform these tasks safely and efficiently is a significant challenge due to the limited accuracy of GPS in such environments. This thesis presents algorithms for pose estimation of quadrotor Micro Aerial Vehicles (MAVs) operating in GPS-denied environments. The main contributions of the thesis stem from the use of the dynamic model describing the motion of a quadrotor as an additional source of information during state estimation.

A state estimator design for quadrotor MAVs that only employs consumer grade inertial sensors is first proposed. Two major improvements to the conventional inertial only state estimators for MAVs are demonstrated. First, it is shown that incorporating an appropriate dynamic model improves the accuracy of the MAV attitude estimate. Second, in contrast to the conventional designs, it is shown that the new estimator provides a drift free estimate of the horizontal components of the quadrotor body frame velocity. These velocity estimates can be exploited to substantially improve the stability and controllability of a quadrotor MAV.

In addition to inertial sensors, monocular cameras provide an excellent source of information that can be used for the MAV state estimation task. The complementary nature of visual and inertial information means that a fusion of the two information sources can improve the accuracy and robustness of the state estimation algorithms. This thesis demonstrates that further improvements in accuracy and robustness can be obtained by incorporating the quadrotor dynamic model into visual-inertial fusion algorithms. The resulting state estimator design is capable of producing reliable pose estimates even when the quadrotor MAV is travelling at a constant velocity, a case which is known to be difficult to handle with conventional algorithms. A theoretical analysis using Lie derivatives is presented to verify this improvement in observability. Extensive simulations and experiments in a number of practical situations are presented to demonstrate the effectiveness of the proposed methodology and to demonstrate that it outperforms conventional visual-inertial fusion methods.

Employing the dynamic model to aid the state estimation can also be extended to deal with wind disturbances that would otherwise hamper the performance of lightweight quadrotor MAVs. This thesis demonstrates that explicit modelling of the effects of wind on the quadrotor dynamics enables the simultaneous estimation of the vehicle pose and two components of wind velocity, using only a monocular camera and an inertial measurement unit. This design is validated through a non-linear observability analysis and extensive simulations that makes use of a realistic wind model. Experimental results in a controlled lab environment are also presented to demonstrate the effectiveness of the proposed state estimator.

Acknowledgements

I am sincerely in debt to my supervisors, Professor Gamini Dissanayke and Associate Professor Sarath Kodagoda, for believing in me and for giving me a freehand to work on my lifelong passion. Their continuous support, guidance and enthusiasm made this feat both achievable and memorable. Thanks for the countless hours of thought provoking discussions, both technical and otherwise, for they were the bits that I enjoyed the most.

I would also like to thank Dr. Zhan Wang and Assistant Professor Steven Waslander for the fruitful discussions and for their continuous encouragement. Thanks also to Professor Robert Mahony for the much enjoyed stay with the ANU Computer Vision and Robotics group.

To all my friends at CAS, thanks for the four years of good laughs, best ever games of badminton and above all, unrivalled comradeship. To all the academic and support staff at CAS, thanks for taking me in and making me part of the family. Never have I felt more at home than in these past four years.

I would also like to thank professor Rohan Munasinghe, for believing that nothing was impossible and for the guidance during the early days of my research. Thanks also to my friends Amila, Yasiru, Shakoor, Mahesh and Senaka for being there with me through thick and thin and for sharing my passion for aerial robotics.

Finally, I am ever in debt to my family who made great sacrifices in making me who I am today.

Contents

Certificate Of Original Authorship	i
Abstract	ii
Acknowledgements	v
List of Figures	ix
List of Tables	xi
Abbreviations	xii
Nomenclature	xiii
Glossary of Terms	xvi
1 Introduction	1
1.1 Micro Aerial Vehicles	1
1.1.1 Multi-rotor MAVs	2
1.2 Motivation and Objectives	3
1.3 Contributions	5
1.4 Thesis Outline	7
1.5 Publications	9
2 Theoretical and Experimental Background	10
2.1 Introduction	10
2.2 Quadrotor MAVs, An Introduction	11
2.3 Frame Definitions and States	12
2.4 Dynamics of a Quadrotor MAV	14
2.4.1 Rigid Body Dynamics	14
2.4.2 Dominant Aerodynamics	15
2.4.2.1 Forces	16
2.4.2.2 Moments	21
2.5 Inertial Sensors	22

2.6	State Estimators	23
2.6.1	EKF Mechanization Equations	25
2.7	Observability	26
2.8	Quadrotor Simulator	29
2.8.1	Visual Simultaneous Localization And Mapping Simulator	32
2.9	Experimental set-up	32
2.10	Discussion	35
3	Model-Aided Inertial Estimators	36
3.1	Introduction	36
3.2	Related Work	37
3.3	Filter Design with Inertial Sensors	40
3.3.1	Conventional Attitude Estimators	41
3.3.2	Model-Aided Attitude and Velocity Estimator	42
3.4	Observability Analysis	46
3.5	Experiments	49
3.6	Discussion and Limitations	52
4	Model-Aided Visual Inertial Fusion	55
4.1	Introduction	55
4.2	Related Work	57
4.2.1	Vision Based Estimation	57
4.2.2	Visual-Inertial Fusion	59
4.2.3	Observability of Visual-Inertial Fusion	61
4.3	Visual-Inertial Fusion Filter Design	63
4.3.1	Conventional Visual Inertial Fusion	66
4.3.2	Model-Aided Visual Inertial Fusion	67
4.4	Observability of Visual-Inertial Fusion	69
4.4.1	Observability of C-VIF	69
4.4.2	Observability of MA-VIF	72
4.4.3	Discussion	76
4.5	Simulations of C-VIF and MA-VIF	77
4.5.1	Simulations with Consistent VSLAM Estimates	78
4.5.2	Simulations with VSLAM Errors	80
4.6	Experimental Evaluation of C-VIF and MA-VIF	82
4.6.1	VIF with Frequent VSLAM Estimates	83
4.6.2	VIF with Sparse VSLAM Updates	83
4.7	Tightly-Coupled MA-VIF	87
4.7.1	Estimation Results	88
4.8	Discussion and Limitations	89
5	Effects of and Estimating Wind	95
5.1	Introduction	95
5.2	Background and Related Work	96
5.3	Wind Model for Simulations	97

5.4	Effects of Wind on State Estimation	98
5.4.1	Inertial Estimators	99
5.4.2	Visual Inertial Estimators	100
5.5	Incorporating the Wind Effects in the Estimator	101
5.5.1	States, Process Model and Measurements	102
5.5.2	Observability Analysis of Wind Affected System	104
5.5.3	Unobservable Modes	107
5.5.4	Removing Unobservable Modes	108
5.5.5	Similarity between MA-VIF and wMA-VIF	109
5.6	Simulations of wMA-VIF	110
5.7	Experimental Evaluation of wMA-VIF	111
5.7.1	Results	114
5.8	Discussion and Limitations	118
6	Conclusions	121
6.1	Summary of Contributions	122
6.1.1	Quadrotor MAV Dynamic Model	122
6.1.2	Model-Aided Inertial Estimators	122
6.1.3	Model-Aided Visual-Inertial Fusion	122
6.1.4	Model-Aided State Estimation amidst Wind Disturbances	123
6.2	Discussion of Limitations	123
6.3	Future Work	125
	Appendices	126
A	Estimating the Propeller Drag Coefficient	127
B	ID Monocular SLAM and Tightly-Coupled MA-VIF	129
B.1	Inverse-Depth monocular SLAM	129
B.2	Tightly-coupled Model-Aided Visual-Inertial Fusion	131
	Bibliography	134

List of Figures

2.1	A typical quadrotor MAV	11
2.2	Motion Primitives for a quadrotor MAV	12
2.3	Coordinate frame definitions	13
2.4	A quadrotor in forward motion	18
2.5	Advancing and retreating blades of a propeller	19
2.6	Lift induced drag of an aerofoil	19
2.7	ARDrone Quadrotor used for experiments	33
2.8	Vicon motion capture setup.	34
2.9	Setup used for ARDrone experiments	35
3.1	3D flight path of the ARDrone experiment	50
3.2	MAVE attitude estimates of ARDrone	51
3.3	CAE attitude estimates of ARDrone	51
3.4	Attitude estimation errors of the MAVE and CAE	52
3.5	MAVE velocity estimates of ARDrone	52
3.6	CAE velocity estimates of ARDrone	53
3.7	Velocity estimation errors of the MAVE and CAE	53
4.1	Coordinate frame assignment for VIF	64
4.2	Structure of a loosely-coupled Visual-inertial fusion set-up	64
4.3	True position and velocity of C-VIF and MA-VIF simulations	78
4.4	2D projection of the VSLAM position estimates and ground truth for the first simulation	78
4.5	Velocity estimation errors of C-VIF and MA-VIF simulations	79
4.6	Scale estimates of C-VIF and MA-VIF simulations	79
4.7	VSLAM position estimates and 2D projection of C-VIF and MA-VIF estimates	80
4.8	Scale estimates of the C-VIF and MA-VIF simulation	81
4.9	2D projection of part of VSLAM position estimates used for ARDrone experiments	83
4.10	Position and velocity estimates of loosely-coupled MA-VIF experiments	84
4.11	Position estimation errors of the loosely-coupled MA-VIF and C-VIF experiments	85
4.12	Position and velocity estimation errors of the loosely-coupled MA-VIF and C-VIF experiments with 1Hz VSLAM	86
4.13	Structure of a tightly-coupled Visual-inertial fusion set-up	88

4.14	Tightly-coupled MA-VIF position estimates and errors	90
4.15	Tightly-coupled MA-VIF velocity estimates and errors	91
4.16	Tightly-coupled MA-VIF attitude estimates and errors	92
5.1	True inertial frame wind velocities used for simulations	98
5.2	Estimation errors of the MAVE from constant wind simulations	99
5.3	Estimation errors of the MAVE from wind gust simulations	100
5.4	Estimation errors of the MA-VIF from wind simulations	101
5.5	Estimation errors of the wMA-VIF from constant wind simulations	111
5.6	Estimation errors of MA-VIF and wMA-VIF for wind gust simulations	112
5.7	True wind velocities and wind velocity estimation errors of wMA-VIF	113
5.8	Setup for wind disturbed experiments	113
5.9	Simulated VSLAM position and orientation measurements	114
5.10	Position estimates of wMA-VIF and MA-VIF for the wind disturbed experiments	115
5.11	Velocity estimates of wMA-VIF and MA-VIF for the wind disturbed experiments	116
5.12	Scale estimates for the wind disturbed experiments	117
5.13	Wind velocity estimates of the wMA-VIF	117
5.14	Velocity estimation errors of wMA-VIF and MA-VIF for the wind disturbed experiments	119
5.15	Accelerometer bias estimate of the wMA-VIF and MA-VIF	120

List of Tables

2.1	EKF Mechanization Equations	27
2.2	Parameters used in first simulator	30
2.3	Noise variances used in both simulators	32
3.1	Conventional Attitude Estimator	43
3.2	Model-Aided Attitude and Velocity Estimator - Initial Design	45
3.3	Model-Aided Attitude and Velocity Estimator - Final Design	49
4.1	VIF observability constraints	62
4.2	Conventional Visual-Inertial Fusion Estimator	67
4.3	Model-Aided Visual-Inertial Fusion Estimator	68
4.4	Performance of different VIF estimators	87
4.5	Performance comparison of LC and TC MA-VIF implementations	89
5.1	Model-Aided Visual-Inertial Fusion Estimator with Wind States	103
5.2	Modified Model-Aided Visual-Inertial Fusion Estimator with Wind States	110
B.1	Tightly-Coupled Model-Aided Visual-Inertial Fusion Estimator	133

Abbreviations

BLDC	Brush-Less Direct Current
CAE	Conventional Attitude Estimator
C-VIF	Conventional Visual-Inertial Fusion
EKF	Extended Kalman Filter
GPS	Global Positioning System
ID	Inverse Depth
IMU	Inertial Measurement Unit
MAV	Micro Aerial Vehicle
MAVE	Model-aided Attitude and Velocity Estimator
MA-VIF	Model-Aided Visual-Inertial Fusion
MEMS	Micro-Electro-Mechanical Systems
NED	North, East, Down
PID	Proportional, Integrative, Derivative
PSD	Power Spectral Density
PTAM	Parallel Tracking And Mapping
RGB	Red, Green, Blue
RMS	Root-Mean-Square
SIFT	Scale-Invariant Feature Transform
VIF	Visual-Inertial Fusion
VSLAM	Visual Simultaneous Localization and Mapping
VTOL	Vertical Take-off and Landing
WGN	White Gaussian Noise
wMA-VIF	Wind incorporated Model-Aided Visual-Inertial Fusion

Nomenclature

General Formatting Style

$f(\dots)$	A scalar valued function
$\boldsymbol{f}(\dots)$	A vector valued function
$[\cdot]_x$	The x component of a vector
$[\cdot]_y$	The y component of a vector
$[\cdot]_z$	The z component of a vector
${}^B[\cdot]$	The frame of expression of a vector
$\dot{[\cdot]}$	The time derivative of a variable
$[\cdot]^T$	Transpose of a vector or a matrix
$\ \cdot\ $	The magnitude of a vector
$E[\cdot]$	The expectation of a random variable
$[\cdot](p, q)$	The $(p, q)^{th}$ element or block of a matrix
$[\cdot](p, :)$	The p^{th} row or row block of a matrix

Specific Symbol Usage

$\mathbf{0}_n$	$n \times n$ all zero matrix
$\{E\}$	Earth fixed inertial coordinate frame
$\{B\}$	Body coordinate frame
\boldsymbol{a}	A vector containing the measurement of accelerometer triad
${}^B_E R$	Rotation matrix to transform a vector from $\{B\}$ to $\{E\}$
c_Q	propeller torque coefficient
c_T	Lumped thrust coefficient
d	Distance from the centre of mass of the quadrotor to propeller hub

d_i	Induced drag coefficient
\bar{D}_L	Lumped parameter drag coefficient matrix
\mathbf{e}_i	The i^{th} unit vector
\mathbf{F}	Sum of aerodynamic forces affecting the quadrotor MAV
f_T	The magnitude of the thrust vector
\mathbf{g}	Gravity vector
g	Magnitude of gravity vector
\mathbf{h}_{vp}	VSLAM position estimates
\mathbf{h}_{vo}	VSLAM orientation estimates
\mathbf{I}_n	$n \times n$ identity matrix
J	Inertia matrix of the quadrotor MAV
k_1	Lumped drag coefficient
\mathbf{M}	Sum of aerodynamic moments affecting the quadrotor MAV
m	Mass of the quadrotor MAV
M_i	i^{th} motor
\mathbf{p}	Position of the quadrotor MAV
r_p	The radius of a propeller
\mathbf{u}	Inputs to a dynamic system
\mathbf{v}	Velocity of the quadrotor MAV
\mathbf{v}_w	Velocity of the wind
\mathbf{v}_∞	Free stream velocity of the quadrotor MAV
\mathbf{X}	State of a dynamic system
\mathbf{x}_i	3D position of an environmental feature in $\{E\}$
\mathbf{y}	Measurements of a dynamic system
ϖ_i	Rotational rate of i^{th} propeller
Θ	Orientation of $\{B\}$ with respect to $\{E\}$
ϕ	Roll angle
θ	Pitch angle
ψ	Yaw angle
Ω	Instantaneous rotational rate of $\{B\}$ with respect to $\{E\}$
Ξ	Matrix that transforms instantaneous rotational rates to Euler rates

ω_g	A vector containing the measurement of gyroscope triad
β_g	Gyroscope bias
β_a	Accelerometer bias
η_g	Gyroscope measurement noise
$\eta_{\beta g}$	Gyroscope bias drift noise
η_a	Accelerometer measurement noise
$\eta_{\beta a}$	Accelerometer bias drift noise
η_q	Process noise
η_r	Measurement noise
η_v	Process noise of the quadrotor translational dynamics
η_p	Noise in VSLAM position estimates
η_o	Noise in VSLAM orientation estimates
η_λ	VSLAM scale drift noise
η_w	Wind velocity drift noise
Υ	A 2×3 matrix consisting of the first three rows of \mathbf{I}_3
$\mathbf{\Gamma}$	3×3 matrix of all zeros with the (3,3) element set to one.
λ	Scale of VSLAM estimates
Λ	3×3 Identity matrix with the (3,3) element set to zero

Glossary of Terms

Attitude	The combination of roll and pitch angles.
Consistent estimates	Estimates whose errors agree with the error covariance bounds predicted by the estimator.
Features	Distinctly identifiable points in an image of a 3D environment.
Free stream velocity	Velocity of an object with respect to the air stream around it.
Induced drag	A drag force that occurs due to the redirection of an air stream by a moving object.
Inertial Sensors	Sensors based on inertia. Common examples are accelerometers and gyroscopes.
Model-aided state estimation	Employing dynamic models and kinematic constants of a platform to aid the state estimation processes.
Monocular VSLAM	VSLAM algorithms that only employs measurements from a RGB camera.
Multi-rotor	A category of aerial vehicles with three or more lift producing propellers.
Observability	The ability to uniquely determine the state of a dynamic system with a causal sequence of measurements.
Pitch	Second Euler angle caused by a rotation around body frame y axis.
Pose	The combination of position and orientation of an object in 3D space with respect to a reference coordinate frame.
Quadrotor	An aerial vehicle with four lift producing propellers.

Roll	Third Euler angle caused by a rotation around body frame x axis.
Scale	The ratio between the true and estimated map by a monocular VSLAM algorithm.
Visual-inertial fusion	The combination of information obtained from visual and inertial sensors to estimate states of interest.
Yaw	First Euler angle caused by a rotation around body frame z axis.